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Task 3: Customer Segmentation / Clustering

Perform customer segmentation using clustering techniques. Use both profile information (from Customers.csv) and transaction information (from Transactions.csv).

You have the flexibility to choose any clustering algorithm and any number of clusters in between(2 and 10) Calculate clustering metrics, including the DB Index(Evaluation will be done on this). Visualise your clusters using relevant plots. Deliverables: A report on your clustering results, including: The number of clusters formed. DB Index value. Other relevant clustering metrics. A Jupyter Notebook/Python script containing your clustering code.

[2]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, davies_bouldin_score
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns

# Step 1: Load data
customers_df = pd.read_csv("Customers.csv")
transactions_df = pd.read_csv("Transactions.csv")

# Step 2: Data Preparation and Merging
merged_df = pd.merge(customers_df, transactions_df, on="CustomerID")

# Step 3: Feature Engineering
# 1. Calculate purchase frequency
merged_df["purchase_frequency"] = merged_df.
 ↪groupby("CustomerID")["TransactionID"].transform("count")

# 2. Calculate recency (days since last purchase)
merged_df["last_purchase_day"] = (
    merged_df.groupby("CustomerID")["TransactionDate"].transform(pd.
 ↪to_datetime).max()
    - pd.to_datetime("today")
).days
```

```python
# 3. Calculate total purchase amount
merged_df["total_purchase_amount"] = merged_df.
 ↪groupby("CustomerID")["TotalValue"].transform("sum")

customer_data = merged_df.drop_duplicates("CustomerID")[["CustomerID",␣
 ↪"purchase_frequency", "last_purchase_day", "total_purchase_amount"]]

# Step 4: Data Scaling
scaler = StandardScaler()
scaled_data = scaler.fit_transform(customer_data[["purchase_frequency",␣
 ↪"last_purchase_day", "total_purchase_amount"]])

# Step 5: Clustering - KMeans (You can experiment with other algorithms)
inertia = []
silhouette_scores = []
db_indexes = []

for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)

    # Calculate metrics
    inertia.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(scaled_data, kmeans.labels_))
    db_indexes.append(davies_bouldin_score(scaled_data, kmeans.labels_))

# Step 6: Plot the Inertia and Silhouette Score to help determine the optimal␣
 ↪number of clusters
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(range(2, 11), inertia, marker='o')
plt.title('Inertia (Sum of Squared Distances to Centroids) vs Number of␣
 ↪Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')

plt.subplot(1, 2, 2)
plt.plot(range(2, 11), silhouette_scores, marker='o', color='orange')
plt.title('Silhouette Score vs Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Silhouette Score')

plt.tight_layout()
plt.show()

# Step 7: Select the optimal number of clusters based on metrics
optimal_k = 4
```

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kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(scaled_data)

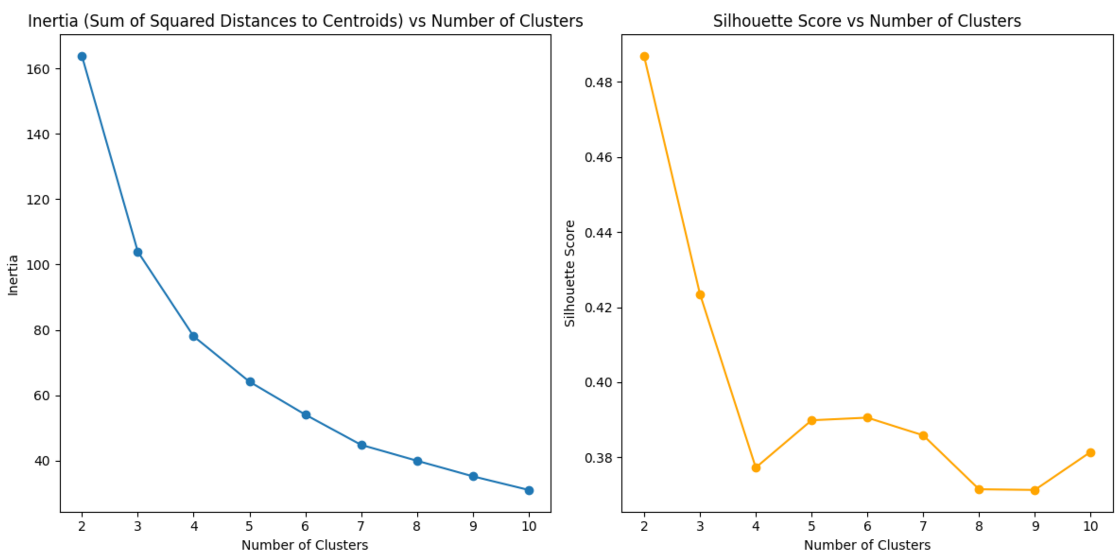
# Step 8: Assign cluster labels to the customer data (only customer-level data)
customer_data["cluster"] = kmeans.labels_

# Step 9: Merge cluster labels back into the original dataframe
merged_df = merged_df.merge(customer_data[["CustomerID", "cluster"]],␣
 ↪on="CustomerID", how="left")

# Step 10: Cluster Visualization using PCA (2D representation)
pca = PCA(n_components=2)
pca_components = pca.fit_transform(scaled_data)

plt.figure(figsize=(8, 6))
sns.scatterplot(x=pca_components[:, 0], y=pca_components[:, 1],␣
 ↪hue=customer_data["cluster"], palette="Set2", s=100, alpha=0.7)
plt.title(f'Customer Segments (PCA) - {optimal_k} Clusters')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend(title='Cluster')
plt.show()

# Step 11: Report the Clustering Metrics
print(f"Optimal number of clusters: {optimal_k}")
print(f"Davies-Bouldin Index: {db_indexes[optimal_k - 2]}")
print(f"Silhouette Score: {silhouette_scores[optimal_k - 2]}")
```



Optimal number of clusters: 4
Davies-Bouldin Index: 0.8595340221510472
Silhouette Score: 0.37724079925410997